SJSU SAN JOSÉ STATE UNIVERSITY

Department of Applied Data Science

DATA 225

Database Systems for Analytics

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GROUP PROJECT REPORT

U.S. Climatological data analysis in Google Cloud Platform

Group 4

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Abstract:

The phrase ‘Under the weather’ has an interesting origin story. Meaning unwell or feeling worse than usual, the term under the weather is a nautical term from the days of old sailing ships. Any sailor who was feeling ill would be sent below deck to protect them from the weather. Being below deck, the sailor would literally be under the weather. Earth’s temperature has risen by an average of 0.14° Fahrenheit (0.08° Celsius) per decade since 1880, or about 2° F in total and the rate of warming since 1981 is more than twice as fast: 0.32° F (0.18° C) per decade [source]. As weather conditions affect all of us in multiple ways and as we’re beginning to experience the effects of climate change, it would be fair to say that we’re all ‘under the weather’ in some way! The role of weather data is critical in numerous applications, including predicting weather patterns, studying climate change, and understanding local weather conditions. In this research project, we are focused on the U.S. Local Climatological Data obtained at a station level from the National Oceanic and Atmospheric Administration (NOAA). Through comprehensive analysis of historical data combined with near-real-time data, we would like to answer the questions listed below:

1. What is the trend of weather patterns over time across the US?
2. Are there zones/clusters of regions where climate change is more prominent than others?
3. What areas in California can utilities companies such as PG&E focus their efforts on to address the surge in demand ahead of time in a data-driven manner? (to reduce stress on the power grid in peak power consumption periods like winter and snowfall)

Solution Requirements:

We propose using the clustering algorithm k-means to identify groups of regions with similar climate change magnitudes. By leveraging these techniques, we aim to contribute to the advancement of weather prediction and climatology. The analysis aims to quantify the impact of climate change, represent this in an intuitive visual manner, and help in predicting future weather conditions in the state of California. Our project shows the possibilities of utilizing the US climatological data to get useful insights through cutting-edge analytical techniques, statistical modeling, and visualizations.

Limitations:

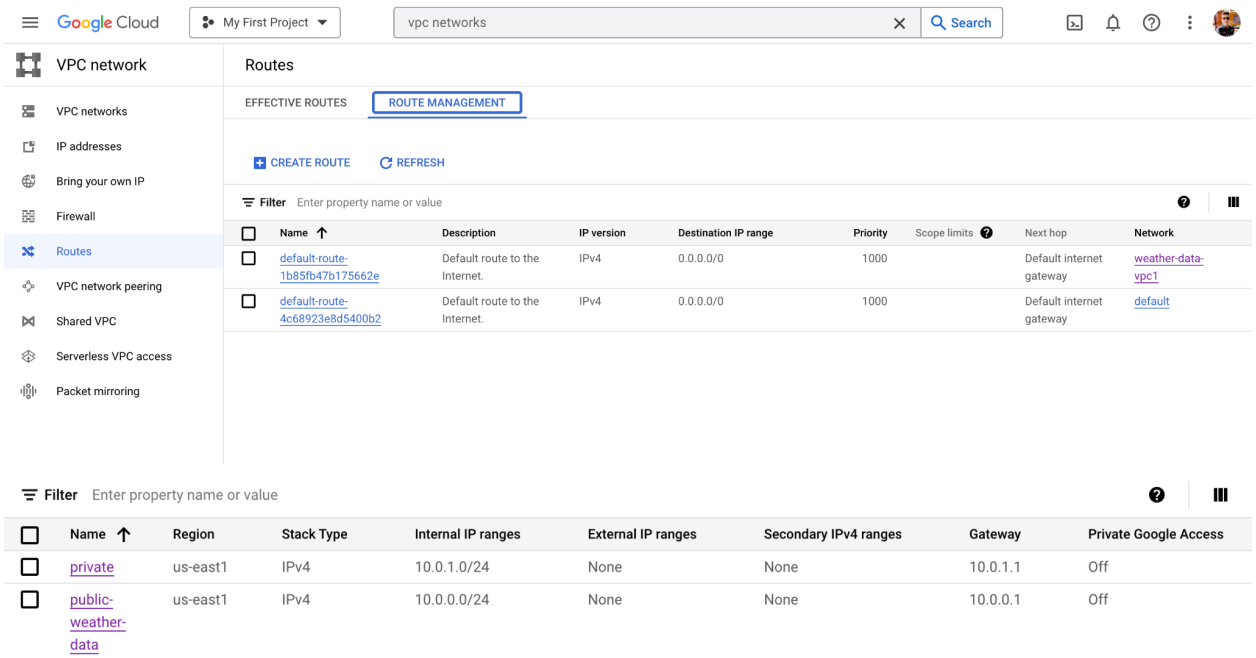
- The dataset's scope might be constrained, missing important long-term patterns. The reliability of analyses is a function of the data quality.
- Non-climatic elements that can affect weather patterns, such as urbanization, deforestation, and industrial activity, might not be taken into account in the analysis.
- The granularity of the analysis may vary depending on how frequently data is collected (daily, monthly, or annually, for example).
- This analysis does not consider the influence of other factors like deforestation and industrial activity that may also have an impact on weather patterns.

Data overview:

In order to efficiently handle and retain our archived meteorological data, we made use of the Google Cloud Platform (GCP). Because a BigQuery instance can handle structured data well ,a characteristic that many climate data sets share, we established a privately owned VPC network to house our entire data workflow, ensuring efficient and safe data handling. A private virtual private cloud (VPC) is needed because it provides a safe and private network environment necessary for handling meteorological data and removes the possibility of data manipulation by unauthorized users. This protects our database from any security threats and external exposure and also enhances the network speed.

In our VPC network, we added two subnets. The deployment of these subnets gives us comprehensive control over the traffic flow and administration within the VPC and contributes to the network's efficient organization.

We have included the gateways and routing table in the pictures given below.



ETL pipelines

We built an ETL pipeline on the Google Cloud Platform; this process necessitates thoughtful preparation and the appropriate GCP tool selection. We have extracted the data from the ftp server (Index of /pub/data/ghcn/daily/by_year) to BigQuery to store and analyze data. Data extraction from various sources is the first step in the ETL pipeline. After that, information is transformed using tools like (Dataflow or Dataprep). After that, BigQuery is loaded with the converted data.Top focus is given to security, which is managed by stringent data encryption techniques and IAM. Cost-effectiveness and resource efficiency are the main goals of the entire procedure.This methodology satisfies the requirements of contemporary data administration and analysis by offering a reliable and adaptable way to manage a variety of data analytics jobs in GCP.

Scheduling using Apache Airflow

In our project, the ETL (Extract, Transform, Load) pipeline is coordinated using Apache Airflow. Utilizing the Directed Acyclic Graph (DAG) script architecture provided by Airflow, we are able to orchestrate the flow of data across specific tasks defined by us.By defining tasks and dependencies in DAG, it ensures that tasks are run in the correct order and at the right time. These Python-written DAG scripts ensure efficient execution for both real-time and archived data sources .

We have created 2 DAGs - one for historical data and one for real-time data as shown in the representation below.

Historical data workflow:

- For historical weather data, we're first extracting yearly data for the last 4 years from the NOAA CDO FTP site (link)
- These files contain weather data at a day level for weather stations from 180 countries, hence we use Python to filter for only US weather data and filter for only temperature, snow and precipitation metrics
- These files are then stored in Cloud storage buckets
- Through Airflow (implemented in GCP as Composer), we're able to schedule a DAG to pick up these files from the storage bucket, perform basic transformation like deduplication and some null value treatment and then write this to a pre-defined schema in BigQuery
- BigQuery is GCP's data warehousing tool which can be used to store and query massive amounts of data within seconds, we use standard SQL as the querying language of choice
- Queries written for specific analyses are then visualized in Looker, GCP's visualization tool

<Placeholder for DAG screenshot>

Real-time data workflow:

- For real-time data, we're first extracting data lagged by 7 days from the current date (for better data coverage) NOAA CDO web services API (link) only for California stations by filtering for FIPS:06 criteria
- These raw data API extracts contain multiple weather parameters all appended horizontally, these need to be filtered for the key metrics of interest and pivoted to be unique at weather station and day level - these will be done through Python
- These transformed dataframes are then stored in Cloud storage buckets for backup purposes
- Through Airflow (implemented in GCP as Composer), we're able to schedule a DAG to pick up these files from the storage bucket, perform basic transformation like deduplication and some null value treatment and then write this to a pre-defined schema in BigQuery
- BigQuery is GCP's data warehousing tool which can be used to store and query massive amounts of data within seconds, we use standard SQL as the querying language of choice
- Queries written for specific analyses with near real-time are then visualized in Looker, GCP's visualization tool

<Placeholder for DAG screenshot>

Data warehousing

As explained above, the last step of Apache Airflow is to write data into BigQuery for the design and implementation of our project's Data Warehouse (DW). Our choice of BigQuery stems from its ability to work with both historical and real-time data sources at scale.
Our solution uses BigQuery's robust query engine to perform analytics directly using SQL queries. Creating tables that are part of our studies and analysis into the data warehouse allows us to have a single location for all of our analytical and reporting requirements. This strategy makes sure that we have a single source of all information, along with our data handling being consistent and easier access for different stakeholders.

Database Architecture:

Historical Data:

We have extracted historical data for the 2020–2023 four-year period.Meteorological data pertaining to station id, minimum temperature, average temperature, maximum temperature, snowfall amount, precipitation amount, and temperature variance are all stored.

Mapping Stations:

Information about California's weather stations is presented in a table. It includes the station name, ID, state, and county.

Real-Time Data:

Our datasource provides us with real-time data that we may access.In line with the historical data, we have preserved weather-related metrics such as station_id, TMIN (minimum temperature), TAVG (average temperature), TMAX (maximum temperature), SNOW (snowfall amount), and PRCP (precipitation amount).

<Placeholder for ER diagram>

Functional Analyses:

1.Overall Temperature Over Time: Calculates daily average temperature by converting numeric date format and grouping data by date.

2.Total Precipitation Across Each Station in California by Year: Determines annual total precipitation at each California station by joining weather and station data and grouping by year and station name.

3.Average Temperature of Non-California Stations in December 2022 with No Snow: Finds average temperature for non-California stations in December 2022 where no snow was reported, using left join and date filters.

4.Total Precipitation and Average Temperature for Selected Stations in 2022: Computes average temperature and total precipitation for 2022 at stations identified by state code, focusing on data within the year.

5.Yearly Snowfall Trends per Country: Calculates annual total snowfall for each country by extracting year from date and summing up non-null snowfall values.

6.Heavy Snow and Rainy Days Analysis: Determines the count of heavy rainy and snowy days by setting thresholds for precipitation and snowfall, grouped by date.

7.Rainfall Recorded by Each Weather Station by Weekday: Aggregates total precipitation for each weather station by day of the week, formatted from the numeric date.

<Placeholder for real time data query>

Code snippets / Queries for ETL workflow:

1) Overall temperature over time

```
SELECT date,
  DATE(
    DIV(date,10000),
    DIV(MOD(date,10000),100),
       MOD(date,100)
  ) as formatted_date,
  AVG(cast(TAVG as float64)) as avg_temperature
FROM `i-multiplexer-406919.weather_data_historical.weather_data_historical_master`
where TAVG is not null
GROUP BY 1,2
ORDER BY formatted_date;
```

2)

```
select extract(year from date_formatted) as year, station_name, SUM(total_precipitation) as
total_precipitation from
  (SELECT   DATE(
    DIV(date,10000),
    DIV(MOD(date,10000),100),
       MOD(date,100)
  ) as  date_formatted, s.station_name, SUM(coalesce(PRCP,0)) as total_precipitation
  FROM `i-multiplexer-406919.weather_data_historical.weather_data_historical_master` w
  join `i-multiplexer-406919.weather_data_historical.weather_data_station_mapping_california` s
```

```
on upper(concat('GHCND:',trim(w.station_id))) = upper(trim(s.station_id))

3) SELECT w.station_id, AVG(cast (TAVG as FLOAT64)) as avg_temperature
FROM `i-multiplexer-406919.weather_data_historical.weather_data_historical_master` w
  left join `i-multiplexer-406919.weather_data_historical.weather_data_station_mapping_california` s
on upper(concat('GHCND:',trim(w.station_id))) = upper(trim(s.station_id))
where (coalesce(SNOW,0) = 0 or SNOW is null)
and s.station_id is null
and DATE(
    DIV(date,10000),
    DIV(MOD(date,10000),100),
        MOD(date,100)
  ) between '2022-12-01' and '2022-12-31'
  and TAVG is not null
GROUP BY 1
order by 2 desc;

4) select LEFT(station_id,5) AS state_code,
AVG(cast(TAVG as float64)) as avg_temperature,
SUM(coalesce(cast(PRCP as float64),0) ) as total_precipitation
FROM `i-multiplexer-406919.weather_data_historical.weather_data_historical_master`
where DATE(
    DIV(date,10000),
    DIV(MOD(date,10000),100),
        MOD(date,100)
  ) between '2022-01-01' and '2022-12-31'
  and TAVG is not null
GROUP BY 1;

5) SELECT country_code, EXTRACT(YEAR FROM PARSE_DATE('%Y%m%d', CAST(date AS
STRING))) as year, SUM(SNOW) as total_snow
FROM `i-multiplexer-406919.weather_data_historical.weather_data_historical_master`
WHERE SNOW IS NOT NULL
GROUP BY country_code, year;


6) SELECT date,
     COUNT(IF(PRCP > 100, 1, NULL)) AS heavy_rainy_days,
     COUNT(IF(SNOW > 50, 1, NULL)) AS heavy_snow_days
FROM `i-multiplexer-406919.weather_data_historical.weather_data_historical_master`
GROUP BY date;


7) SELECT station_id,
     FORMAT_DATE('%A', PARSE_DATE('%Y%m%d', CAST(date AS STRING))) AS weekday,
     SUM(PRCP) as total_precipitation
FROM `i-multiplexer-406919.weather_data_historical.weather_data_historical_master`
```

```
GROUP BY station_id, weekday
ORDER BY station_id, weekday;
```

Statistics and Machine Learning:

Using the massive amount of weather data at our disposal, we were interested in 3 key data science use cases:

- Is there a difference between temperatures over the years
- Is temperature for a given year normally distributed
- Are there groups of stations in California that show similar extreme weather patterns (heavy rainfall and snow) that could help utility companies in focusing their efforts to ensure limited power disruptions during extreme weather events

Use case 1: Difference between temperature over years

To do this, we first considered the median of TAVG (avg temperature) across all stations for each day of year for 2021 and 2022. Our hypothesis was that there would be a significant difference between these 2 years' temperatures. To test this, we ran a t-test with our null hypothesis being "There is no significant difference between the temperatures of 2021 and 2022", hence our alternative hypothesis becomes "There is a significant difference between the temperatures of 2021 and 2022". The code snippet for our t-test is shown below:

```
# Converting date string to date format for 2022
weather_data_us_2022['clean_date'] = pd.to_datetime(weather_data_us_2022['date'], format='%Y%m%d')

# Converting date string to date format for 2021
weather_data_us_2021['clean_date'] = pd.to_datetime(weather_data_us_2021['date'], format='%Y%m%d')
```

```
# Taking median temperature for all US for the year 2022
df_weather_temp_grouped_2022 = weather_data_us_2022[['clean_date','TAVG']].groupby('clean_date')[['TAVG']].median()
```

```
# Taking median temperature for all US station for the year 2021
df_weather_temp_grouped_2021 = weather_data_us_2021[['clean_date','TAVG']].groupby('clean_date')[['TAVG']].median()
```

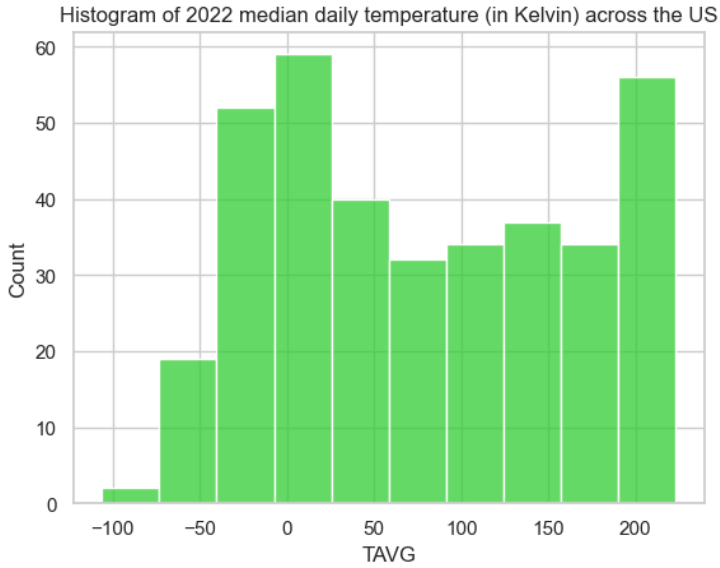
```
_, p_value = ttest_ind(df_weather_temp_grouped_2022['TAVG'].head(282)
                       , df_weather_temp_grouped_2022['TAVG'])
print(f"p-value for independent t-test between 2022 and 2021 median temperature by day is: {p_value}")
```

```
p-value for independent t-test between 2022 and 2021 median temperature by day is: 0.0036704045290449705
```

The outcome was that the p-value for the independent t-test was lower than the critical value i.e. 0.05, indicating that we have sufficient evidence to reject the null hypothesis and conclude that **there is a significant difference between 2021 and 2022 temperatures.**

Use case 2: Distribution of temperature

We wanted to understand if median daily temperature across 2022 follows a normal distribution or not. To prove or disprove this mathematically, we used a Shapiro-Wilk test. In the Shapiro-Wilk test, null hypothesis = Sample is from the normal distributions.(p-value>0.05). Hence, if we obtain a p-value > 0.05, we accept the null hypothesis and can conclude that the data is normally distributed.
First, we visually inspected the histogram of the daily median temperature and the plot looked like the below chart:



Through visual inspection of the data, we see a somewhat bimodal distribution of data and this doesn't look like a bell curve. We can confirm our suspicion by running the Shapiro Wilk test.

```
shapiro_weather_data = shapiro(df_weather_temp_grouped_2022['TAVG'])
shapiro_weather_data
```

```
]: ShapiroResult(statistic=0.9386388063430786, pvalue=3.915789914543666e-11)
```

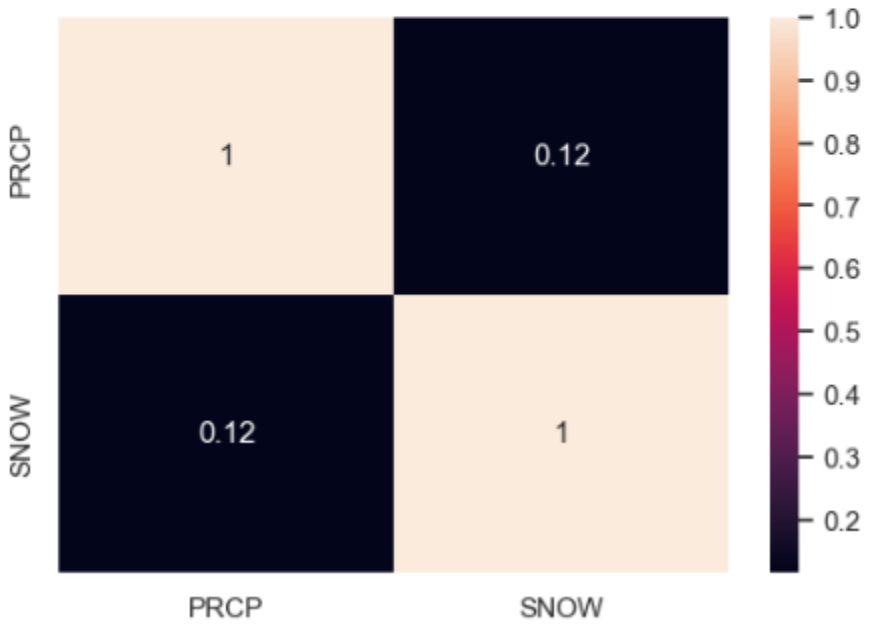
The p-value <0.05 implying that we reject the null hypothesis and can conclude that the data is NOT normally distributed.

Use case 3: Extreme weather data clustering for California stations
California is one of the most geographically diverse states in the US. Despite being a coastal state, there are several dry-desert like areas but also snowy mountains and picturesque beaches. Hence, for such a unique region, it is essential for utility companies like PG&E (California's largest utilities provider) to understand weather patterns in order to be prepared for seamless power supply even in extreme conditions.
In order to do this, we propose a novel approach of using k-means clustering to identify clusters or groups of stations that have similar precipitation and snowfall conditions.
For this, we considered 756 weather stations in the state of California for which we had good coverage of precipitation (total precipitation for year 2022) and snowfall (average yearly snowfall) data.

WIth this, we ran a kmeans clustering algorithm to understand the groups of stations that showed similar weather patterns. The steps are explained below.

- After aggregating 2022 data for 756 stations (sum of precipitation and average of snowfall), we first checked if these are correlated

```
# Heatmap to illustrate relationships between all independent variables

# Setting size of figure with width 10 and height 8
plt.figure(figsize=(6,4))

# Calculating the correlation matrix on the numeric columns
corr_weather_2022 = df_weather_cali_grouped[['PRCP', 'SNOW']].corr()

# Plotting the heatmap
sns.heatmap(corr_weather_2022, annot=True)

# Displaying the heatmap
plt.show()

# No correlation observed between the variables
```

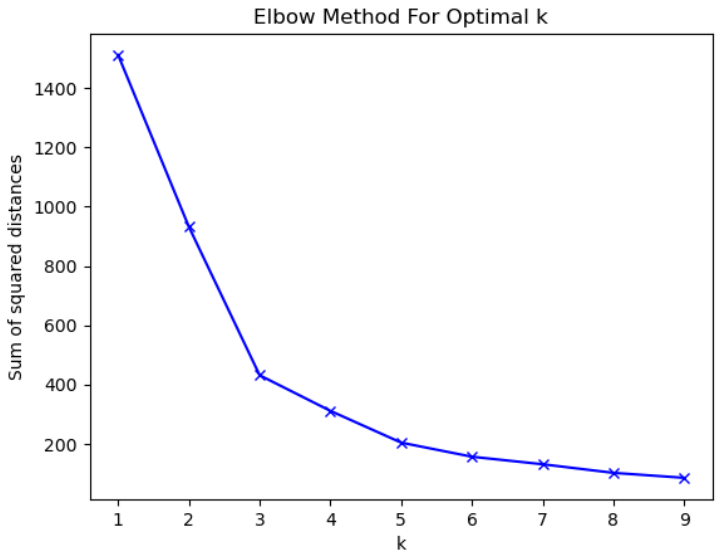


- Since the correlation was quite low, we can proceed with the next step of scaling the data - for this, we used StandardScaler from scikitlearn

```
# Select the relevant columns for clustering
weather_data_clustering = df_weather_cali_grouped[['PRCP', 'SNOW']]

# Correlation and remove correlated features
# No correlation

# Standardize the data
scaler = StandardScaler()
weather_data_scaled = scaler.fit_transform(weather_data_clustering)
```

- K-means is an unsupervised machine learning algorithm wherein we can cluster datapoints that have similar characteristics
- Since we don't know how many clusters we will get at the end, we first need to iterate through different values of k and find the optimal value - this is done through a method called the elbow curve, wherein we plot the different values of k against the sum of squared distances (SSD) between each point from the respective cluster centroids
- Optimal value of k is chosen based on the "elbow" point or the point beyond which the rate of decrease of SSD is not as gradual

```
# Elbow curve to get optimal value of k
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans

# Calculate sum of squared distances
ssd = []
K_value_range = range(1,10)
for k in K_value_range:
    km = KMeans(n_clusters=k)
    km = km.fit(weather_data_scaled)
    ssd.append(km.inertia_)

# Plot sum of squared distances / elbow curve
plt.plot(K_value_range, ssd, 'bx-')
plt.xlabel('k')
plt.ylabel('Sum of squared distances')
plt.title('Elbow Method For Optimal k')
plt.show()
```



- From our iteration, we can say that the optimal value is 5 although this is subjective and open to interpretation
- With k=5, we can run kmeans as shown below to get the data labeled with 5 clusters

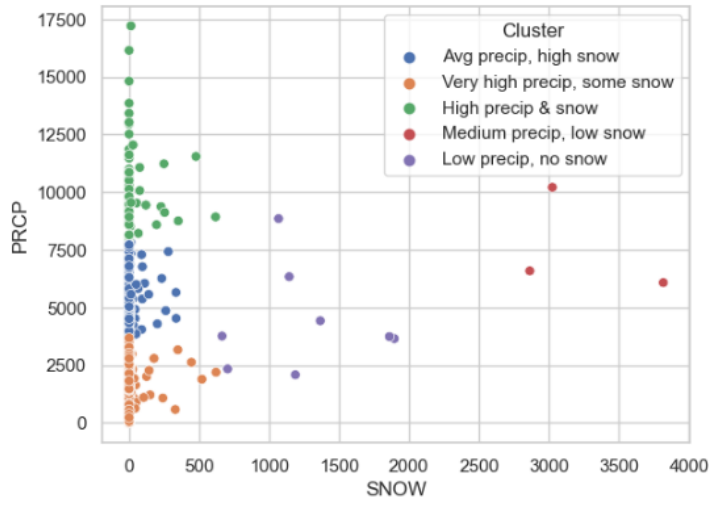
```
# Perform KMeans clustering
kmeans = KMeans(n_clusters=5)  # Choosing the number of clusters based on elbow plot
kmeans.fit(weather_data_scaled)

# Add the cluster labels to the original dataframe
df_weather_cali_grouped['cluster'] = kmeans.labels_

# Save the dataframe with cluster labels to a new CSV file
df_weather_cali_grouped.to_csv('weather_data_california_clustered.csv', index=False)
```

- Based on analyzing the clusters, we can observe that there each station can show 1 among 5 characteristics
    a. Very high precipitation with some snow - wet regions
    b. Low precipitation with no snow - dry habitable regions
    c. High precipitation and snow - extreme regions
    d. Average precipitation and high snow - snowy regions
    e. Medium precipitation with low snow - habitable regions

```
# Defining labels for clusters
kmeans_cluster_number = [
    df_weather_cali_grouped['cluster'] == 0,
    df_weather_cali_grouped['cluster'] == 1,
    df_weather_cali_grouped['cluster'] == 2,
    df_weather_cali_grouped['cluster'] == 3,
    df_weather_cali_grouped['cluster'] == 4
]

kmeans_labels = ['Very high precip, some snow', 'Low precip, no snow', 'High precip & snow',
                 'Avg precip, high snow', 'Medium precip, low snow']

# Creating a new label column based on mapping cluster number to label
df_weather_cali_grouped['cluster_label'] = np.select(kmeans_cluster_number, kmeans_labels)
```

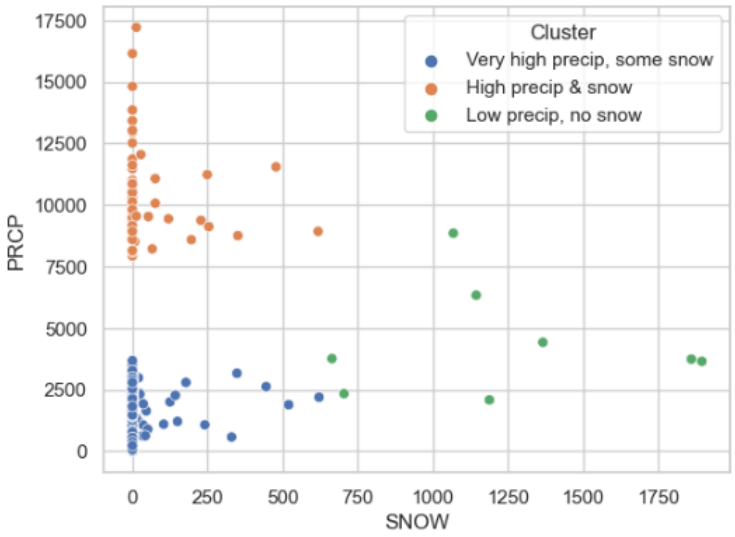
Visualizing the results, we can observe that clusters d & e are outliers - these are the few extreme regions that PG&E must focus on. However, they also skew our results and hence, we can visualize the clusters without these outlier points to get a better view of the data spread.

```
# Set the style of the visualization
sns.set(style="whitegrid")

# Creating a bubble plot
bubble_plot = sns.scatterplot(data=df_weather_cali_grouped, x="SNOW", y="PRCP",
                              hue="cluster_label", legend="full", palette="deep")

# This is getting skewed by 2 clusters

# Find the handles and labels of the current legend
handles, labels = bubble_plot.get_legend_handles_labels()

plt.legend(title='Cluster')
# Show the plot
plt.show()
```



Visualization of the data without the outlier points:

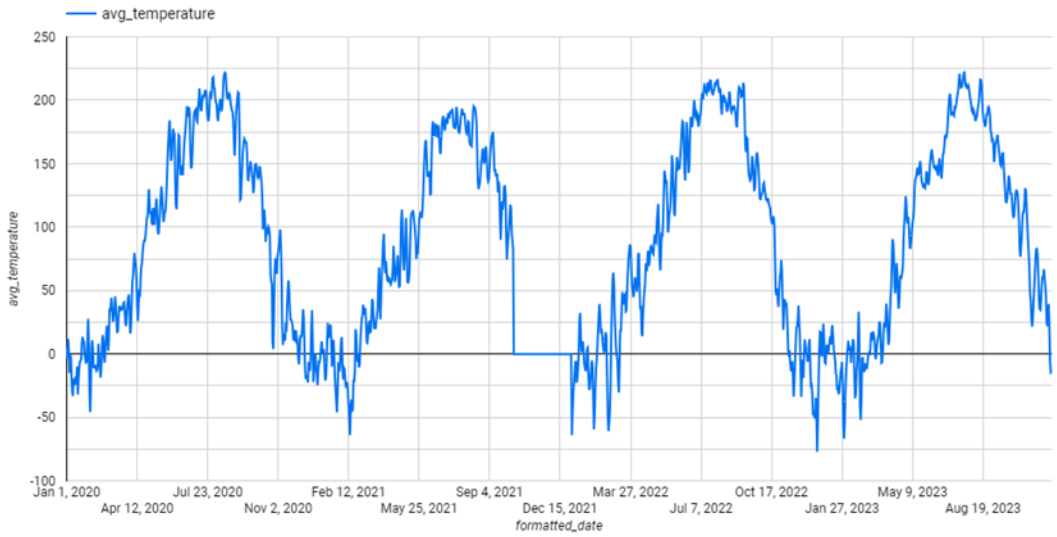
```
# Set the style of the visualization
sns.set(style="whitegrid")

# Excluding outlier clusters
cluster_df = df_weather_cali_grouped.loc[df_weather_cali_grouped["cluster"] != 3]
cluster_df = cluster_df.loc[cluster_df["cluster"] != 4]

# Creating a bubble plot
bubble_plot = sns.scatterplot(data=cluster_df, x="SNOW", y="PRCP",
                              hue="cluster_label", legend="full", palette="deep")

# This view is a bit more spread out after removing the clusters with extreme values

# Find the handles and labels of the current legend
handles, labels = bubble_plot.get_legend_handles_labels()

plt.legend(title='Cluster')
# Show the plot
plt.show()
```



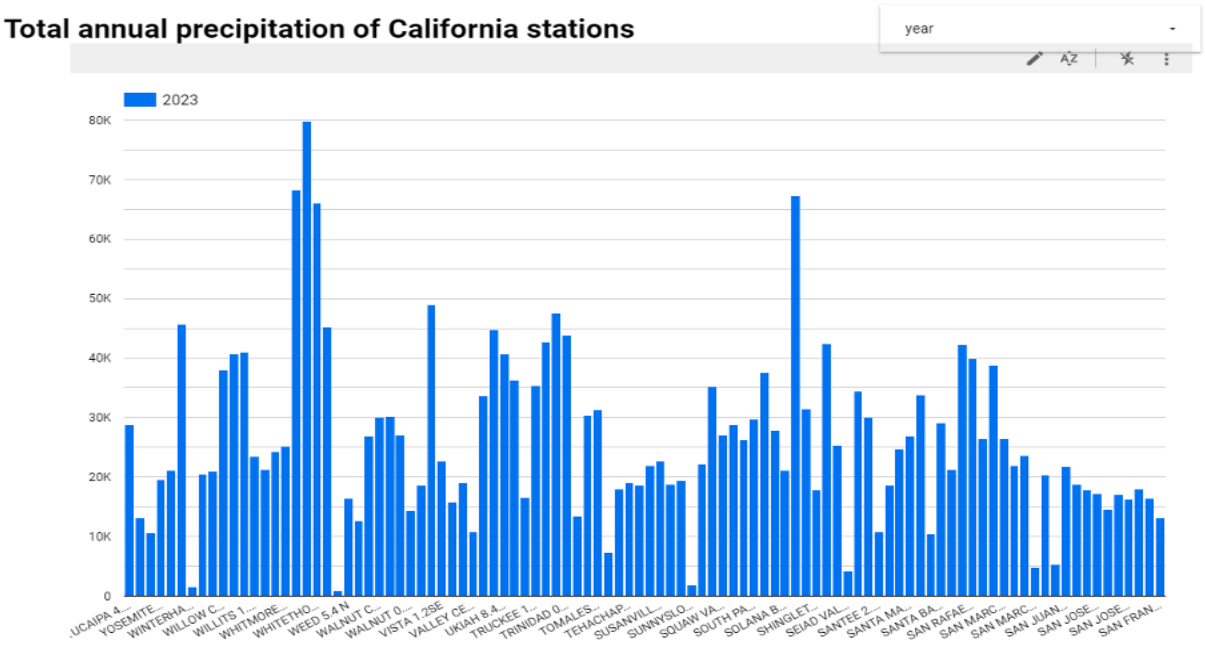
Business Intelligence:

We have successfully completed business intelligence tasks in our project, concentrating on extracting the important observations, following thorough data processing and analysis done in the previous steps. We made the decision to combine our BigQuery searches with Looker from Google Cloud Platform in order to efficiently illustrate these observations. This choice is driven by Looker's strong data visualization features and its smooth BigQuery integration, which guarantee not only that our complex datasets are accessible but also clearly understandable.

Historical average temperature trends across the last 3 years across the USA



The line graph shows the variations in the average temperature in the US during a period of three years, starting in January 2020 and finishing in late August 2023. The data shows a recurring pattern in which the temperature rises in the middle of the year, which corresponds to the summer months, and falls at the start and end of the year, which corresponds to the colder months of winter.



The Y-axis of the graphic shows the total annual precipitation for each weather station, while the X-axis shows the various weather stations.The bars show how much precipitation was measured at each station; some had considerably larger totals than others, reflecting variations in the distribution of rainfall in California.

Avg temperature of non-California weather stations with reports of no snow in December 2022

	station_id	avg_temperature
1.	USR0000ACHL	
2.	USR0000ACOV	
3.	USR0000ADEN	
4.	USR0000ADON	
5.	USR0000AFOU	
6.	USR0000AGEO	
7.	USR0000AHAY	
8.	USR0000AHBR	
9.	USR0000AHIL	
10.	USR0000AHOG	
11.	USR0000AHON	
12.	USR0000AIMY	
13.	USR0000AKIA	
14.	USR0000ALAK	
15.	USR0000AMOL	
16.	USR0000ANOO	
17.	USR0000APRO	
18.	USR0000APTM	

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The X-axis shows the matching average temperatures for December 2022 for each weather station listed by station ID on the Y-axis. The average temperature recorded at each station is represented by the length of each bar, which shows a comparison of temperatures across different areas that did not report any snowfall during the month.

Avg temperature and total precipitation for 2022 for select state stations

state_code	avg_temperature	total_precipitation
USW00	128.86	2,297,916
USR00	107.74	0
USC00	60.24	4,285
USS00	41.07	7,707,756

The chart has two sets of horizontal bars on the X-axis that show the average temperature and total precipitation for each state station, and a list of state codes on the Y-axis. The first set of bars represents the average temperature in degrees for the year 2022, and the second set depicts the total amount of precipitation in an undefined unit for the same period. The length of the bars varies, representing the variations in temperature and precipitation between the states.